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Solar parking lot management: An IoT platform for smart charging EV fleets, using real-time data and production forecasts

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A B S T R A C T

The fast transition to the electrification of the energy system, combined with an exponential growth of the market share of electric vehicles, is leading to a tight interrelation between electric energy production and transportation, two prominent sectors in fossil fuels consumption and greenhouse gas emissions. Accelerating this process, the management of electric fluxes, aiming at optimizing production and demand coupling, plays a crucial role in reaching the net-zero emission target. The proposed software platform is designed to optimally manage the energy fluxes for a solar powered parking lot, serving a fleet of electric vehicles; the real-time knowledge of energy production and demand, in conjunction with forecasted power generation, allows the maximization of renewable energy self-consumption, thus reducing the exchange with the external grid. The software platform can work either in design mode, allowing the dimensioning of the various parking lot components, or in real-time mode managing instantaneously the energy balance. As a case study, it is tested on the 2019 parking lot mobility data of a research center, assuming a complete transformation of the then existing fleet of employees' cars to electric vehicles. A comparison of the resulting energy flows with those projected by an established commercial tool is performed, as well as a preliminary economic evaluation. Both consistency of the simulation results and favorable economics validate the presented smart charging algorithm and Internet of Things platform for the real-time energy management of a solar parking lot.

1. Introduction

The steep growth of anthropogenic greenhouse gas (GHG) emissions related to the use of fossil resources requires fast and challenging solutions; transportation and electricity production sectors are responsible for around two thirds of global CO_2 emissions. According to the numbers published by the U.S. Energy Information Administration (EIA) in its monthly energy review of August 2022 [1], the total consumption of primary energy in the U.S.A. in the year 2021 was 28.5 Million terawatt-hours (TWh) or 2.4546 Billion tonnes of oil equivalent (toe), 7.9 Million TWh (0.6782 Billion toe) of which are used by the transportation sector and 10.8 Million TWh (0.9267 Billion toe) by the electric power sector. 94% of the total energy used for transportation came from petroleum and natural gas and 6% from biofuels and electricity [2]. In 2021, according to EIA estimates [3], cars, light trucks, and motorcycles accounted for the largest shares of total U.S. transportation sector energy consumption, with light-duty vehicles (cars, small trucks, vans, sport utility vehicles, and motorcycles) accounting for 54.2%, commercial and freight trucks 4.5%, jets, planes, and other aircraft 8.7%, boat, ships, and other watercraft 4.6%, trains and buses 2.6%, the military sector 2.0%, pipelines 2.8%, lubricants 0.5%. Globally, carbon dioxide emissions associated with transportation accounted in 2021 for 7620 Mt; 600 Mt less than pre pandemic level by 2019 [4].

Since the onset of the industrial revolution, ever increasing amounts of GHG have been released into the atmosphere. While the energy mix and corresponding supply chains shifted from coal to oil and more recently towards natural gas, the prosperity of humankind still relies on fossil fuels and energy conversion systems based on fuels combustion. Even today, transportation and electricity production are heavily reliant on CO_2 emitting technologies. But there is a silver lining, as technological improvements coupled with a strong cost reduction enabled the fast growth of the total installed energy capacity of renewable energy sources for electricity production (RES-E). Together with powerful battery energy storage systems (BESSs), they will impose drastic changes in these two historically conservative sectors. Today, the fast growth of electric vehicles (EVs) related technologies, as well as their forecasted market penetration, reaching the record of 6.6 million vehicles sold in 2021 [5], generates new scenarios impacting the electric energy production and transportation market. Based on existing climate-focused

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List of abbreviations and units

GHG	GreenHouse Gas
EIA	Energy Information Administration
TWh	TeraWatt hours
TOE	Tonnes of Oil Equivalent
RES-E	Renewable Energy Sources for Electricity production
BESS	Battery Energy Storage System
EV	Electric Vehicle
HEV	Hybrid Electric Vehicle
PHEV	Plug-in Hybrid Electric Vehicle
BEV	Battery Electric Vehicle
V2G	Vehicle to Grid
V2V	Vehicle to Vehicle
G2V	Grid to Vehicle
PV	PhotoVoltaic
SPEM	Solar Parking of Electric vehicles Management
CMC	CRS4 Microservice Core
IoT	Internet of Things
LCOE	Levelized Cost Of Energy
MPC	Model Predictive Control
PCC	Point of Common Coupling
CU	Control Unit
CMS	Charging Management System
BMS	Battery Management System
SOC	State Of Charge
OPEX	OPerational EXpenses
CAPEX	CAPital EXpenses
ICE	Internal Combustion Engine
kWh	kiloWatt hours
kWp	kiloWatt peak
CHP	Combined Heat and Power
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ME	Mean Error

policy pledges and announcements, the International Energy Agency predicts for 2030 EVs to represent more than 30% of vehicles sold globally across all modes (excluding two- and three-wheelers) and the global electricity demand for EVs to reach 1100 TWh; then about 4% of the total final electricity demand [5].

Albeit the forecasted electricity demand for EVs accounts only for a minor share, the increasing interconnection between electrical energy generation and mobility with the associated environmental impact, will generate both new opportunities and challenges for stabilizing the energy grid, on both local and wider regional level [6]. The integration of these two sectors will be crucial in the transition to a decarbonized system, creating new applications for the smart management of base load coupling intermittent electric energy sources and temporally flexible EV charging demand.

Building, optimizing and managing new energy systems, in which fossil fuels assume ever decreasing importance, opens a path to a more climate sustainable future. Electricity markets with a high share of RES-E require additional back-up capacity to meet the target generation reliability criterion. Recently, this topic received much attention from the European Union in general, and the European Network of Transmission System Operators for Electricity in particular [7].

One key component for the success of such integrated systems is the so-called smart grid approach. Many studies have assessed the economic value that can be created by a smart grid, e.g., by providing flexibility services to the electricity system, by addressing the power quality, and by lowering both peak demand and system costs [8]. The latter are all measures suitable to reduce the negative impacts of fluctuating supply and demand of electric energy caused by RES-E and EVs charging.

In this context, the electric mobility sector, with its various forms of hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), battery electric vehicles (BEVs), and their possibility to operate both in vehicle to grid (V2G) and grid to vehicle (G2V) modes, paves the way for a new paradigm of strongly coupled electricity and mobility sectors, which vice-versa opens new avenues to tackle temporal imbalances between energy production and demand [9,10]. On the one hand, without smart management the impact of EV charging on the grid costs and stability could be quite relevant; see for example highway fast-charging stations [11]. On the other hand, new and fast evolving technologies such as BESSs, smart metering, and digital communication infrastructures, candidate photovoltaic (PV) parking as an aggregator able to manage the electricity market participation of a vehicle fleet and present a framework for optimizing the charging and discharging of EVs, thus minimizing the effect of the intrinsic intermittency of PV power on the distribution network. A micro-grid can be seen as a decentralized group of electricity sources, loads and BESS that normally operates connected to, and synchronous with, the traditional wide area electricity grid, but is able to disconnect for a certain amount of time and function autonomously in island mode. RES-E powered EV parking lots, where the energy fluxes can be directly controlled and managed in a micro-grid, can operate semi-autonomously or even autonomously from the main power grid, whenever it is favorable under physical or economic conditions.

In the last decade, this topic has become of crucial interest both in industry and academia; many publications addressed the coupling of electricity and mobility sectors, analyzing various aspects of the problem [12–17].

Several numerical approaches and algorithms have been proposed in order to optimize the managements of the energy fluxes between renewable energies production and EVs fleets: linear programming [18–21], model predictive control [22,23], artificial intelligence (AI), machine learning and game theory [24–26], Monte Carlo and statistical methods [27–29], and more empirical approaches [30–32]. Many papers also focus on the economic aspect of energy fluxes management aiming to minimize the electricity exchange with the grid and connected instabilities [33–36].

This work focuses on the optimal design and real-time management of EV fleet charging in a grid connected parking lot with a dedicated solar PV plant coupled with a BESS.

For this purpose, a software platform named SPEM - Solar Parking of Electric vehicles Management – including system architecture and algorithms, has been developed on top of a microservice architecture framework named CMC – CRS4 Microservice Core[1] – and its dedicated general-purpose Internet of Things (CMC-IoT) microservice [37].

One of the main characteristics of SPEM is given by the possibility to time shift the EVs charge using the forecast of PV production according to remaining parking time, energy demand and future energy production. Charging of any individual EV can be deferred to optimize the overlap between production and demand PV production forecast is here considered to be provided from commercial or open external service.[2] More generally, energy fluxes can be managed with the goal to minimize, and possibly avoid, energy exchange with the external grid, or to purely maximize the economic revenue by minimizing the Levelized Cost Of Energy (LCOE) used for internal load and EV charging.

This paper puts emphasis on EV fleet charging for company

[1] https://github.com/smartenv-crs4/cmc.

[2] https://solcast.com, https://solarwebservices.ch, https://solargis.com.

employees with full time employment and limited office opening hours. Demand is not considered as dispatchable, i.e., each EV connected to a charger is charged without exceptions, the same day before leaving the parking lot. Grid connection and a sufficiently sized BESS set aside the need to sell the energy production to EV owners at any moment and at any price. In this context, demand management through price signals, as described in Ref. [38], is not the primary method of choice to achieve maximum use of auto produced renewable energy. Since the future flux of EVs to the parking lot is considered as unknown, a formal optimization of energy fluxes for the present and future time frames cannot be run to make optimum decisions. Instead, a suitable rule-based system that dynamically manages the charging power over time is proposed, according to a defined best interest of parking lot operator and EV owners. The introduction of a demand managing price [38], offered only in hours of surplus production and triggering the charging of dispatchable demand, i.e., charging of EVs not urgently in need of energy, is a simple and elegant measure to shift demand not only within a day but also from one day to another. Such a system can be complementary to the one described in this paper. It could be easily added, but in this work the choice is to keep the analysis of the results as simple as possible and to limit the number of assumptions made regarding energy demand and other EV owner preferences.

The paper is outlined as follows. Following this introduction, Section 2 provides a detailed description of the SPEM software platform; in Section 3 a realistic case study is presented, based on a research center in Sardinia, Italy. The results obtained with SPEM are compared to results generated with the commercial software Homer Grid® [39] that, according to HOMER® Energy LLC, "*combines engineering and economics to rapidly perform complex calculations enabling you to compare design outcomes and consider options for minimizing project risk and reducing energy expenditures*". In Section 4 a preliminary economic analysis for the case study is performed, while Section 5 is dedicated to the discussion and concluding remarks.

2. SPEM system description

The goal of the SPEM platform is to merge and analyze all the information about mobility data, grid pricing and renewable energy supply forecast, to optimally run the operation of a solar EV parking lot under various stakeholder's objectives. The electric energy fluxes are handled based on a dynamic model of the operation process, representing single components as linear empirical sub models obtained by system identification [40,41].

Starting from the battery performance deterioration control - through calendar life and cycle life management - it is then suitable to apply a model predictive control (MPC) algorithm that can be adapted relatively painlessly to a changing operating environment by updating its predictive models to match the changes in the patterns of load and generated power [42]. Basically, what MPC does is to optimize each current time by taking a finite number of future time steps, the so-called time horizon, into account. Stepping forward, the time horizon is then shifted into the future, all input variables, including forecasts, are updated and the iterative model-based optimization is repeated.

The management of internal energy fluxes within the microgrid - consisting of EVs fleet, PV plant and BESS - and the potential energy exchange with the external grid is determined by the operator's preferences, ranging between maximum autonomy and maximal economical revenue. Besides the utility tariff, the environment in which the EV parking lot is operating strongly impacts energy management. In most cases, the EV parking lot subsystem constitutes a microgrid that is coupled by a single connection point to the external grid. This connection point could be either a single point of common coupling (PCC), in the case of direct connection with the distribution grid, or a node when connected to a company's internal grid. In the first case, if for whatever reasons, energy exchange and particularly energy sales to the external grid are undesired, the self-consumption of auto-produced RES-E might become a priority; in the second case, if a variable internal load of significant size must be satisfied, peak shaving [43] or demand response [44,45] approaches seeking to adjust the demand for power instead of adjusting the supply could play a dominant role for the energy management and, last but not least, for the dimensioning of PV power plant and BESS.

2.1. Solar EV parking lot

The main components of a solar EV parking lot are:

- PV power plant
- EV charging stations
- Internal DC bus
- Battery storage system (BESS)
- Load connection

These elements constitute the microgrid environment shown in Fig. 1, together with auxiliary components embedded for the optimal set up of the system. There are three different converters dedicated to facilitating and optimizing the electricity flows (in red) within the system, one control unit (CU) sending and receiving data (in blue) to/from all the parking lot components, in particular to the charging management software (CMS), which in turn is connected to the charger and the various EV battery management systems (BMSs) of the connected EVs, which, for the sake of simplicity, are here depicted as a single box.

Each system component shown in Fig. 1 has its own specific characteristics that influence the operation of the microgrid under analysis. Since this work deals with the optimal electricity management among these different components, their main properties are, for the sake of simplicity, assumed constant or linearly dependent on a few basic parameters. Since data management, associated with weather forecasts and vehicle mobility, is the driver of the system optimization, the focus here lies on the control system and related algorithms. The SPEM platform is the core of the Control Unit (CU) that collects all the real time information from sensors and manages all the devices actuators. For choosing single components such as DC-DC converter, solar panel type or BESS from the vast number of products and vendors on the market, a professional software, such as HOMER® Grid, is recommended, as it offers a huge catalog of different components comprising all the relevant technical characteristics.

2.2. Model data, strategies and goals

As indicated in Fig. 1 by the red double headed arrows, the real time management of the energy fluxes between the various components is related to the instantaneous set of quantitative choices, i.e.,

- Load/discharge BESS.
- Purchase/sell energy from/to the external grid.
- Load individual EVs or defer loading to future.

The current version of SPEM software core does not support the V2G option; however, the possibility of using battery EVs to eventually supply internal or external demand is available in the SPEM platform.

The scenario shown in Fig. 2 generates a complex pattern that is the key element for minimizing the objective function in every given time step. Hence, the goal of SPEM is to provide a dynamic algorithm to optimize the energy management for requisites defined by the parking manager, based on the current state of charge (SOC) of the BESS, the current and future quantity of PV production, and the current and future energy request for EV charging and internal load. As an example, this could mean minimizing the energy for EVs charging when PV production and BESS are scarce, and charging as much as possible EVs and BESS when PV production is high. The three options highlighted in red in Fig. 2 represent energy flows (G2BESS, V2G and BESS2G) which might

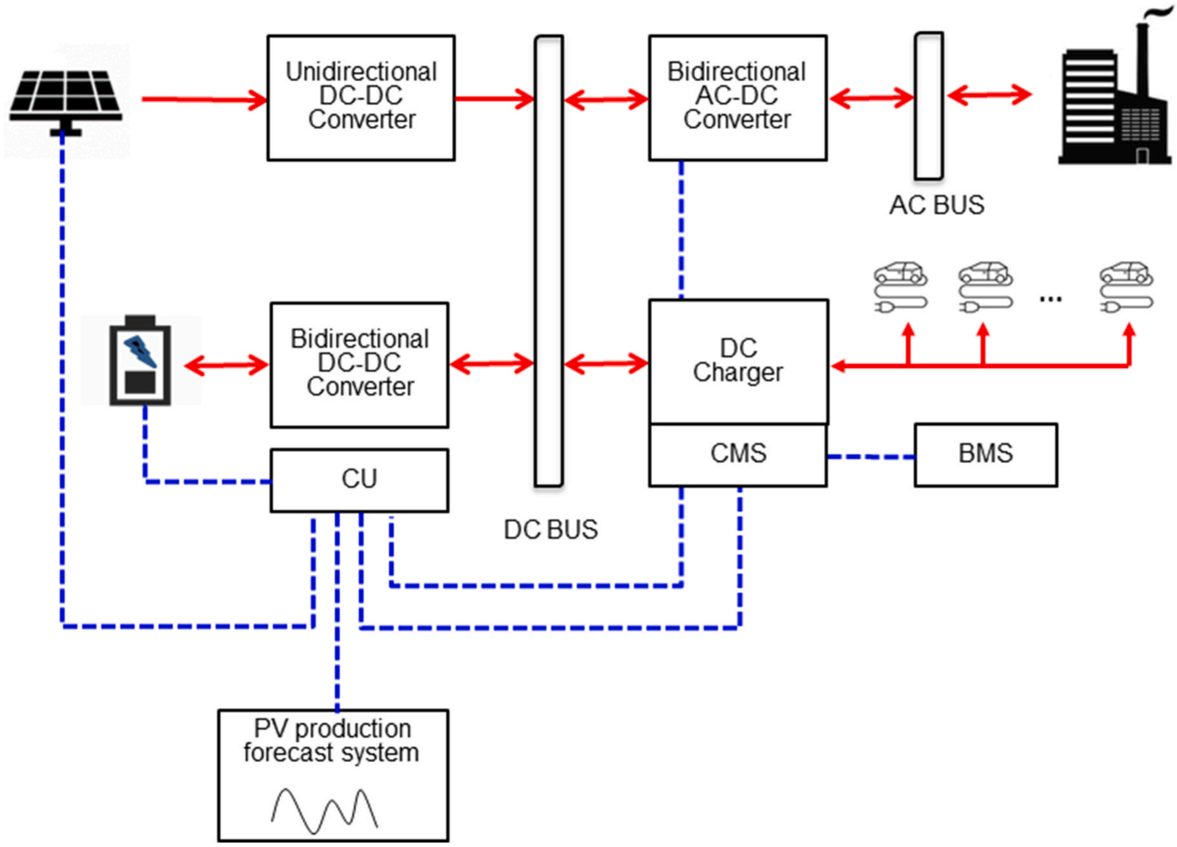

Fig. 1. Design of the emulated microgrid environment of a solar EV parking lot.

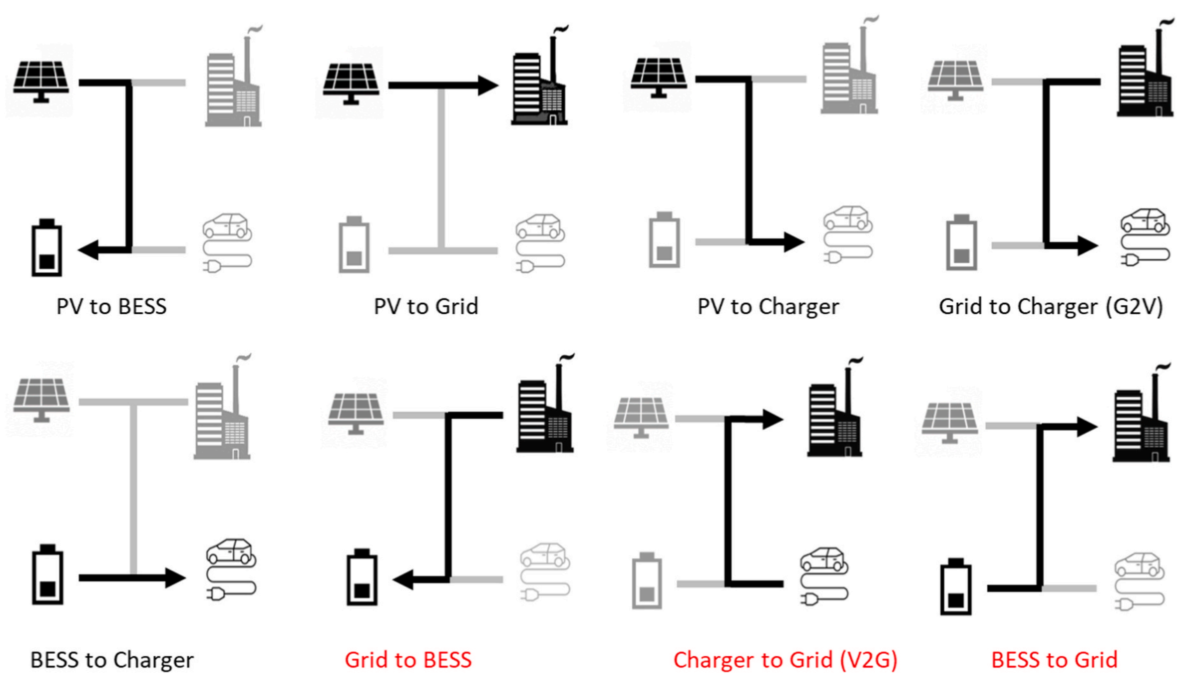

Fig. 2. Eight energy flux options from which energy management can choose in every instant of time. Options in red are not used in SPEM.

be used under specific circumstances - i.e., favorable electricity tariff conditions - could be included relatively easily but are not supported by the presented version of SPEM, since they are not essential for the considered use case.

A common choice is to defer EV charging in the early morning when PV production is momentarily insufficient but is expected to grow fast within the coming hours. In its current implementation SPEM is limited to *segment-wise optimization*, i.e., optimizing charging sessions on a single day rather than *cross-segment optimization*, i.e., shifting energy demands from one day to another, as applied for instance in Refs. [32,38].

The implementation of SPEM software core utilizes a rule-based and purely deterministic algorithm for fleet charging and energy management. Given a certain input, it will always produce the same output, after passing through the same sequence of states. In detail, the algorithm considers the following time dependent variables:

1. Internal load
2. PV production
3. Future PV production
4. State of charge (SOC) of the BESS
5. Charger occupancy
6 Type and SOC of EVs
7 Remaining parking time of EVs
8 Target SOC of EVs
9 Utility tariff

Once this information is known, optimal management of the energy balance can be performed. Considering the previously defined variables, the optimization procedure is generally defined as the pursuit of three quantitative objectives:

- Minimizing net energy import from external grid by maximizing RES-E auto-consumption
- Minimizing peak power demand from external grid
- Minimizing cost by providing a set of dynamic charging tariffs to customers

These three quantitative objectives are not necessarily correlated; this paper focuses on the first two, giving a preliminary economic evaluation based on historical data.

Mandatory user inputs required when connecting an EV to a charging station are the minimum parking time and the minimum SOC at exit. This information, together with other optional customer preferences, such as fast versus slow charging, amount of flexibility regarding final SOC, availability for V2G and maximum accepted charging energy price, will enable the parking manager to control the electricity fluxes accordingly.

2.3. Operational modes

The SPEM software platform has two operational modes: design and real-time.

The design mode serves to find the proper dimensions of all electric components and to verify the correct functioning of the system. At the start, the system pre-processes the expected input data, often historical data, for a given simulation period. It extracts minimum, maximum and average values of important variables such as maximum anticipated charging power, maximum occupation of the parking lot, average internal load per day, minimum parking time, total energy needed for charging and total PV production; these values help to assess if the initial dimensions of crucial components are within reasonable ranges.

During the iterative design phase, accessing various simulated data streams with high accuracy and fine-grained temporal resolution, allows to manage charging and discharging of the EVs batteries, based on a smart charging strategy, which considers the time dependent variables (1) to (8), introduced in the previous section.

Finally, the knowledge of the electricity tariff (9) can be used to calculate power and electricity charges that dominate the operational expenses (OPEX). Together with the capital expenses (CAPEX), the latter data points are inputs for the economic analysis, which is conducted for dimensioning the critical components under economic criteria. This leads to the possibility of providing a preliminary economic assessment.

The real-time mode operates as a real-time charging management software (CMS); all the signals reaching and exiting the control unit are synchronized within a user defined time interval. For every time interval, the algorithm processes data (1)–(8) regarding the current state of the system for managing energy fluxes. In this mode, all these data are readings from instruments measuring electric energy flows as well as systems/sensors detecting user related information, e.g., entrance/exit time, minimum SOC of the battery at the exit. Besides the current state of the system, also a forecast of future PV production is used to better manage the parking lot, particularly in view of the optional deferral of EV charging to later time steps.

Sections 3 and 4 focus purely on the results of the design mode, obtained in a realistic case study. The real-time operational mode is still under active development and will be presented in a second publication together with a small-scale physical model of a real solar parking lot that is under development.

2.4. Charging and deferring algorithm

SPEM employs a simple heuristic rule-based algorithm, which uses only the PV production forecast and some information about the EVs already present, to maximize the usage of auto-produced PV energy for smart charging EVs in a solar parking lot.

The used algorithm does not present the solution of a classical optimization problem, which typically means optimizing a given time frame with all input variables a priori known. In case, this would mean to run, for instance, for every given time step, an optimization, e.g., least squares, of all the manageable energy fluxes for a period that covers all the remaining opening hours of the parking lot. However, this would require a forecast for the mobility data. Predicting number of arrivals, arrival time, EV type, battery status, and departure time lies outside the scope of this publication.

As shown in the flowchart in Fig. 3, the main function is the loop over the time steps. In design mode, it goes through a fixed number of time steps in which the simulation period is divided. Typically, in the design mode a time step of 15 min and a simulation period of one year is used to find, for instance, the ideal size of crucial components like the PV plant or the BESS. Obviously, in real-time mode a time step is much shorter. Its length must be adapted to the sensor readings, which requires the highest sampling rate. In the context of a solar parking lot, this is typically PV production. In real-time mode, the loop over time steps can be seen as an infinite loop where, for every discrete time step, synchronized sensor readings, regarding status of the solar parking lot and future PV production, are updated and subsequently used to calculate optimum quantities for the different energy fluxes that will take place during this time step.

In the design mode, inputs (see 2.2) are commonly historical data files of the simulated time period. From this data, the algorithm tries to optimize the charging power for every car, in every instance of time. The individual charging power can range between maximum charge power allowed by battery (depending on EV type and SOC) and battery charger, and zero, i.e., complete deferring of charging to future time steps. For the deferring decision, the PV forecast for remaining parking time and remaining parking time itself are the key factors. In the analyzed scenario, where EVs arrive mainly in the early morning when little PV auto-production is available, it can be possible to avoid expensive charging from the grid by waiting for more PV to become available later in the day. In such a scenario - typical for office and corporate parking lots - characterized by an average long-stay parking time, a relatively large number of charging stations at low charging power is recommended.

At every instant of time t the power balance must be satisfied, as given by equation:

$$P^t_{pv} + P^t_{load} + P^t_{bess} + P^t_{evs} + P^t_{grid} = 0, \tag{1}$$

with P^t_{pv} being the power production from photovoltaic, P^t_{load} the power to satisfy the internal consumption of the parking lot, P^t_{bess} the power to/from the BESS, P^t_{evs} the power to run the EV chargers and P^t_{grid} the power to/from the grid. In this notation, outflows have a positive sign and

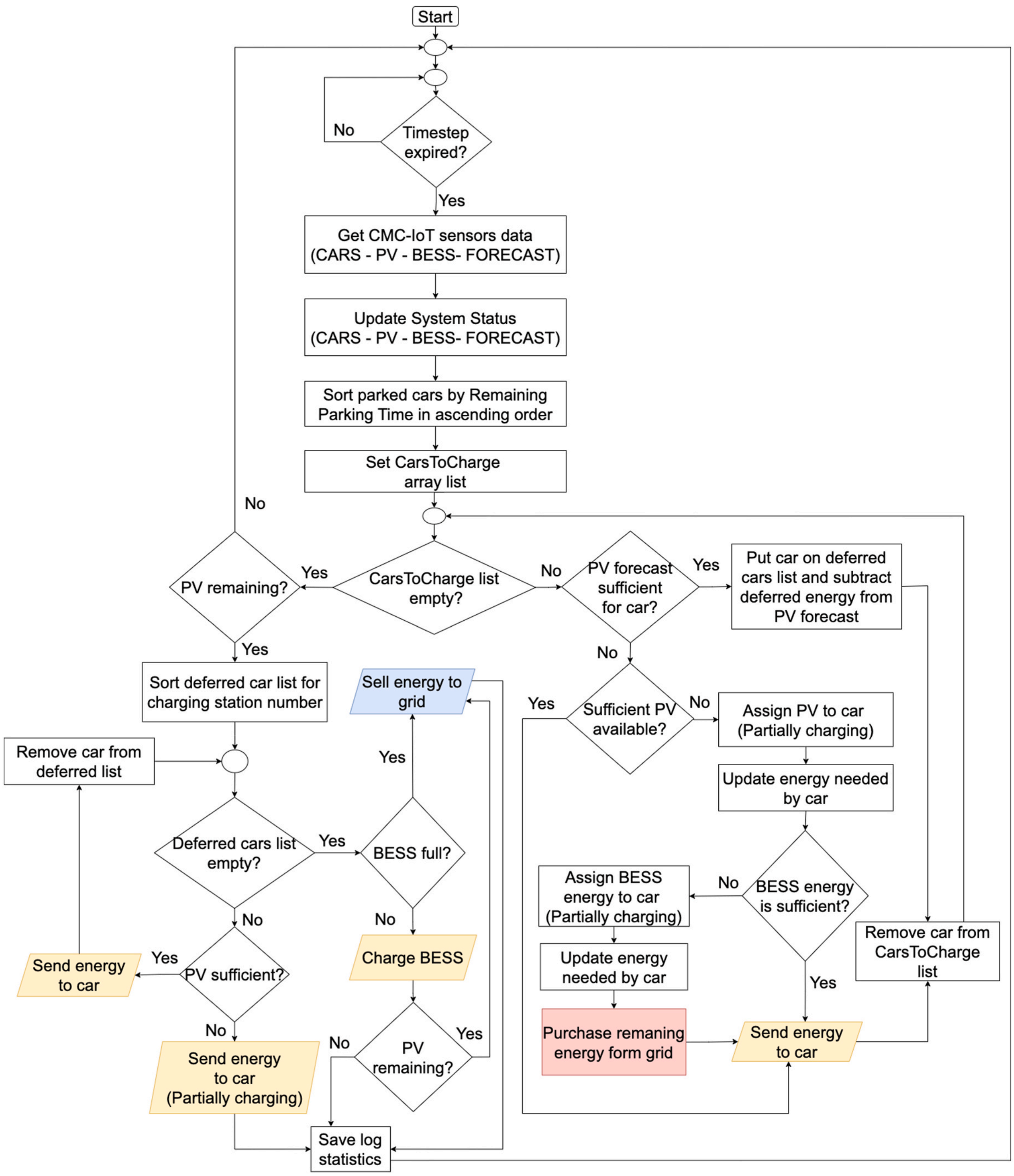

Fig. 3. Charging and deferring algorithm flowchart.

inflows have a negative sign. P_{load}^t must be satisfied first either from PV, BESS or external grid, in this order of priority.

The energy management objective is to minimize the exchange with the grid, shifting in time the power demand for charging the EVs fleet by deferring individual EVs at certain time steps from charging. At the beginning of any time step, t_0, the EVs are initially sorted for remaining parking time in ascending order; then the loop over the EVs starts, meaning that the EVs with the smallest remaining parking time will be handled first. Strictly following this order, the algorithm decides if an EV gets deferred or charged, based on the remaining energy demand of the EV, its exit time and the PV production forecast for future time steps, denoted as $\widehat{P}_{pv}^t$. If the forecasted PV production for the remaining parking time is larger than the remaining energy demand of the EV, it is flagged as deferred. This means that for every individual EV the deferring function is defined as

$$d^n = \begin{cases} 0, \delta E^n < \sum_{t=t_0}^{\tau^n} \left(\widehat{P}_{pv}^t \, \delta t\right) \\ 1, \delta E^n \geq \sum_{t=t_0}^{\tau^n} \left(\widehat{P}_{pv}^t \delta t\right) \end{cases}, \forall 0 < n < N, \qquad (2)$$

with N being the number of EVs present at the beginning of the time step, δt being the length of the current time step, τ^n the index of the exit time of EV n and $\delta E^n = E_{exit}^n - E_0^n$ being the remaining energy demand of EV n, i.e., the difference between the requested SoC at exit time, E_{exit}^n, and the current SoC, E_0^n.

If an EV gets deferred, its *average* power demand for future time steps is subtracted from the power production forecast, $\widehat{P}^{t}_{pv}$, according to the equation:

$$\widehat{P}^{t}_{pv} = \widehat{P}^{t}_{pv} - \frac{\delta E^{n}}{(\tau^{n} - t_0)}, \forall t_0 \leq t < \tau^{n}. \tag{3}$$

the total power needed for charging, P_{ch}, can be written as

$$P_{ch} = \sum_{n=1}^{N} d^{n}\, p^{n}_{ev} = \sum_{n=1}^{N} \left(p^{n}_{pv} + p^{n}_{bess} + p^{n}_{grid} \right), \tag{4}$$

with p^{n}_{ev} the charging power demand of the nth EV and p^{n}_{pv}, p^{n}_{bess} and p^{n}_{grid} the power contributions from the different sources.

For every time step, the charging power demand of each individual EV, p^{n}_{ev}, is defined. It must neither exceed the maximum power limit of the charger, P^{n}_{Cmax} , nor those of the EV battery, P^{n}_{Bmax}. Not exceeding these two limits, the charging power demand for each individual EV is set dynamically, dependent on the total PV power remaining after charging previous EVs in the list, P^{n}_{pv}, the remaining energy demand of the EV, δE^{n} and the remaining time before exit, $(\tau^{n} - t_0)$. Putting all these factors together p^{n}_{ev} is calculated according to the formula:

$$p^{n}_{ev} = Min\left(Max\left(\frac{P^{n}_{pv}\delta E^{n}}{\sum_{n=1}^{N}\delta E^{n}}, \frac{\delta E^{n}}{(\tau^{n} - t_0)} \right), P^{n}_{Cmax}, P^{n}_{Bmax} \right). \tag{5}$$

It is important to note that the term $\frac{\delta E^{n}}{(\tau^{n} - t_0)}$ guarantees that non-deferred EVs are charged even if at the current moment no solar energy is available. Thus, no EV exits the parking lot insufficiently charged, due to a parking period with insufficient solar production.

Subsequently, the algorithm satisfies this power demand for all EVs which are not deferred from the available solar power in the before mentioned order of charging. If for one or more EVs the power demand given by equation (5) cannot be served from PV, power is drawn from the BESS and only if the BESS is exhausted, power is bought from the grid.

However, if there is still PV power available after all EVs, which were not deferred, are served, the remaining PV power is distributed amongst the deferred EVs. If afterwards there is still PV power left, it is stored in the BESS and not before it is completely loaded power is sold to the grid.

For prototyping, the SPEM software was first implemented using the high-level programming language GNU Octave; the code was later ported to JavaScript™ in a microservice architecture for a seamless integration with CMC-IoT.

2.5. Software subsystem and infrastructure

The control system algorithm described in the previous section is part of a more comprehensive software layer acting as backend for the global SPEM platform, which is implemented leveraging the features of CMC-IoT.

CMC-IoT is a general purpose IoT platform, implemented in compliance with the specifications of CMC (CRS4 Microservice Core), which is a high-level software framework based on a microservice architecture aiming to support the development of vertical services and applications. The adoption of a microservice architecture model is able to provide advantages to a complex software system in terms of resilience, maintainability, scalability, modularity, heterogeneity and independence of technology [46–52].

CMC-IoT allows to connect with any IoT device, acting as a middleware for the applications accessing to a device by providing a uniform interface to Things, which in general need a specific driver or connector to be integrated in the platform. This integration is based on HTTP REST (Representational State Transfer) communication approach, meaning that the message exchange among devices and between the IoT subsystem and the other SPEM components is implemented by means of standard HTTP calls identified by HTTP URIs (Uniform Resource Identifiers).

The choice of integrating the optimization algorithm inside an IoT platform is motivated by the need of a straightforward way to model every component of the SPEM system generating input data for the algorithm itself. In this context, modeling means describing each system entity as a CMC-IoT object, in order to implement any data exchange among SPEM components as a communication between CMC-IoT objects.

In fact, as a generic IoT platform, CMC-IoT can be adopted in a wide variety of applicative domains; its data model, based on the concept of Device Type, is fully customizable; as a consequence, users can map their own devices onto custom categories with custom properties. However, it is up to the users to build up a model determining which objects of their domain must be mapped onto the CMC-IoT entities.

The base entity of the data model is the Thing, the physical object hosting one or more Devices, where a Device can be either a sensor capable of measuring a single physical property (e.g., temperature, voltage, pressure), or an actuator executing a single command (e.g., a switch). Each Device is able to perform Observations of an Observed Property (e.g., energy), expressed by a Unit Measure (e.g., kWh). In the SPEM platform, Things are containers hosting the actual sensors and actuators, which generate data from measurements performed on the physical system. For example, the BESS is a physical box modeled as a Thing hosting a number of Devices; each of them acts as a sensor for an electrical parameter such as SoC (energy meter - kWh) and charge/discharge power (power meter - kW).

The most relevant SPEM entities modeled in CMC-IoT are described in the following Table 1.

Using this microservices approach inherited from CMC architecture and exploiting the potential of CMC-IoT, the SPEM platform is robust and flexible enough to be easily scalable and replicable in different contexts and application scenarios.

More importantly, CMC-IoT provides SPEM with an interface to real-word sensors and actuators that, differently to commercial simulation software giving indicative theoretical results, allows SPEM to be integrated in the real time control of a physical system.

3. Reference case

The reference case for managed office charging is the CRS4 research center, located in the south of Sardinia, 42 km away from the regional capital Cagliari, in an industrial park close to the small town of Pula, Italy. The center has about 143 employees, who arrive at work either by bus or by private car. Since the company parking lot is entered and

Table 1
SPEM entities modeled in CMC-IoT.

Things	PV sensoring - actual
	PV sensoring - forecast
	BESS sensoring box
	EV sensoring
Devices	Actual PV sensor
	Forecast PV sensor
	EV distance sensor
	BESS SoC sensor
	BESS charge/discharge sensor
	EV timeslot regulator
Device Types	Power meter
	Energy meter
	Distance sensor type
	Minutes per slot regulator type
Observed Properties (Unit)	Power (kW)
	Energy (kWh)
	Distance (km)
	Timeslot (minutes per slot)

exited by using a personal badge, these data are available. Furthermore, for every employee the home-work distance is known. This information is utilized in anonymized form, for projecting a complete transformation of the workers' vehicle fleet from Internal Combustion Engine (ICE) cars to EVs. For this purpose, the 2019 mobility data (pre-pandemic) have been compiled and used as a historical reference data set. This data set is a typical company's fleet profile; vehicles enter the parking area in the morning and exit after an average stay of 9 h. Few or no vehicles are present during nights, weekends and holidays. Assuming that in the reference case under analysis the average parking time is quite long and the energy demand for the average recharge is about 15 kWh, it was decided to use Level 2 charging stations with a power charge up to 7 kW. This choice is dictated by the fact that during the long stop in the parking lot, EVs charging can be optimized using slow low-power refills; however, the software system can operate with different types of recharging units, smartly mixing slow and fast recharge.

3.1. CRS4 mobility data

The occupancy profile of the parking lot can be considered as one part of the reference mobility profile, the other part being the traveling profile, which mainly depends on the commuting distance of every employee. Fig. 4 shows the average occupancy profile for a typical working week in 2019, compiled from the company badges database. Every weekday is shown as a separate line. For the same week, Fig. 5 depicts the probability density function of EVs parking time, with its peak slightly above 9 h, while Fig. 6 shows the probability density function of EVs daily traveling distance. Most of CRS4's employees arrive from Cagliari, while others come mainly from Capoterra at 20 km distance and Pula at 10 km distance. The total annual number of cars arriving/departing at the parking lot is 12,849 which means on average, calculated over 260 working days per year, 49.42 charging sessions per day.

The battery SOC of each arriving vehicle is calculated from its maximum SOC minus round-trip distance from home to work, plus a standard log-normal distribution [53,54] for private trips, multiplied by an average electric energy consumption of 0.2 kWh per kilometer [55]. The reference value for the charging is 100% of SOC, however customers could choose lower values according to the proposed conditions of the parking manager, based also on the electricity spot market. From this SPEM calculated a yearly energy required for charging of 184,747 kWh with an average energy demand of 14.37 kWh per single charge.

3.2. Reference benchmark: HOMER® grid

In order to perform a preliminary energy balance evaluation of the SPEM tool, a commercial software for designing grid-tied distributed energy projects, named HOMER® Grid [39], is used. Since the July 2020 update, HOMER® Grid can model hybrid systems with EV charging stations, featuring both an on-demand mode, which charges vehicles as fast as possible, and a smart, deferrable mode where EV charging is optimized for the lowest impact on the utility bill. The version released in July 2020 describes the functionality of the EVs charging algorithm as follows:

The EV Charging Design Tool in HOMER® *Grid accepts inputs to describe vehicle types and charging requirements, such as EV battery size (kWh) and maximum charge rate (kW). The software allows a project developer to define how often the charging station is in use through average charge duration time and traffic density over the course of the year.*

The comparison with SPEM was performed using the smart or deferrable charging station mode model of HOMER® Grid, since it fits very well to the managed office charging environment of the reference case. The main difference between HOMER® and SPEM approaches on handling EVs recharge lies in the fact that SPEM is designed to manage the EVs fleet with a deterministic real-time approach, while HOMER® Grid uses a statistical distribution for the mobility data. For this reason, the comparison between HOMER® Grid and SPEM should be rather consistent regarding the integrated data on a yearly basis. The differences should lie in the details and cumulate hopefully in an efficiency advantage for SPEM, deriving from its fine-grained, real-time single session management.

3.3. Parking lot design and energy balance

With the purpose of first designing an optimal system and then comparing the yearly energy balances for this configuration, both with HOMER® and with SPEM, one-year simulations have been performed, using the CRS4 mobility, solar radiation and PV production data for 2019. In order not to allow the internal load to dominate the microgrid, but rather to focus on solar EV charging, it is assumed an internal load much smaller than the actual energy demand of the research center, which features a large high performance computing cluster. In detail, an annual average internal load of 100 kWh per day was set, with an average power consumption of 4.17 kW, a peak consumption of 7.99 kW and a load factor of 0.52. A random variability of 10% day to day and 10% time step to time step is finally introduced.

The parking lot design represents a tradeoff between different objectives, namely economic considerations which favor large PV plants and small BESSs and maximum autonomy, high auto consumption and minimum grid sales which favor small PV plants and larger BESS. The size of the dedicated PV plant and the BESS in the reference case was set to 150 kWp and 300 kWh, respectively; a primary load of 10 kWh per day is assumed as parking lot associated electricity demand. Starting from this load profile, the mobility data and a PV production, estimated by HOMER® from solar radiation, ground temperature and solar panel type, the preliminary energy balance of the parking lot was calculated. The statistical distribution for the fleet management component of HOMER® was adapted to the CRS4 mobility data set used in SPEM, while the PV energy production for SPEM was derived from HOMER® output with 1 h time step, interpolated to a time interval of 15 min.

The yearly energy balances, for the two simulations made with HOMER® and SPEM, are shown in Tables 2 and 3. For this simulation, the forecasted PV production was generated by adding a random variability to the locally measured PV power output 2019 series. This leads to error metrics mean absolute error MAE = 0.17908, mean absolute percentage error MAPE = 0.019726, mean error or bias ME = 0.00044420 [56]; several random variability and confidence levels of the forecasted data have been tested, showing a good stability of the system with respect to the errors in predicting the weather conditions. However, as pointed out in the Introduction, the IoT platform can interface with any kind of forecast data provided by external services.[3]

3.4. Real time data

As pointed out in previous sections, the basic improvement provided by SPEM with respect to HOMER® Grid and other commercial energy modeling software emerges from the fact that SPEM uses a MPC to manage and optimize in real time the energy fluxes between all the system's electric components.

To manage real time information coming from the system components, a given time interval - 15 min in the present case to simplify the results display - must be chosen. Inside this time interval, the SPEM algorithm relies not only on the current data, but also on weather forecasts for PV production.

In the following, simulation results for the reference case are discussed, obtained with HOMER® Grid and SPEM, starting with a comparison of key numbers of the modeled systems, as depicted in Table 4. For reasons that were already mentioned and that will be further

[3] The difference in the energy balance is due to losses, which occur in components, such as BESS and ac-dc/dc-ac converters.

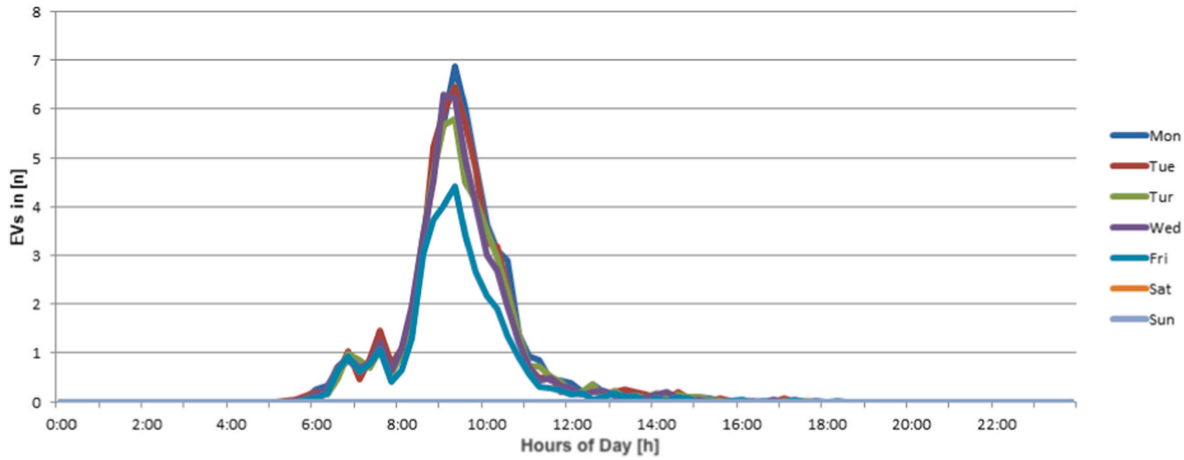

Fig. 4. Yearly average number of arriving cars, over arrival time, for typical work weeks. Every weekday is depicted in a different color.

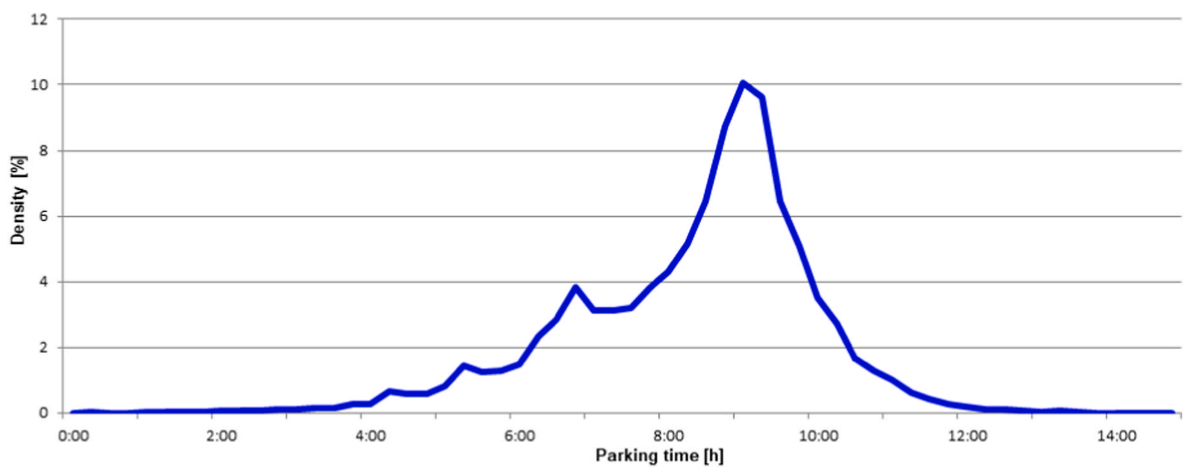

Fig. 5. Probability density function of EVs parking time.

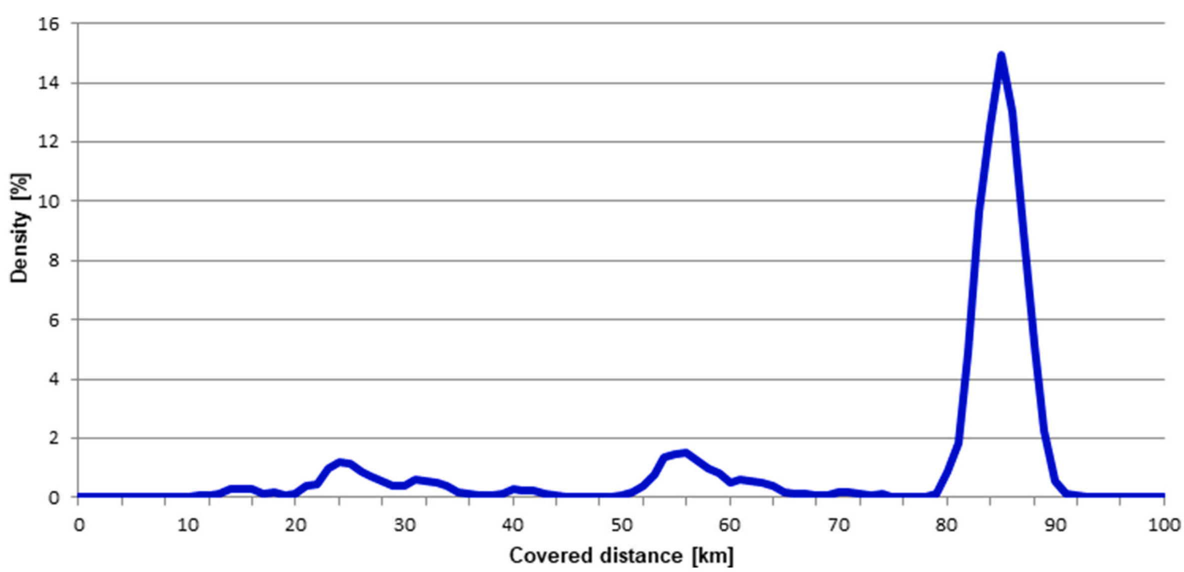

Fig. 6. Probability density function of EVs covered distance.

discussed below, these numbers are very close but not completely identical.

Figs. 7–11 show the one-week evolution (March 25–31, 2019) of the power fluxes profile output of the two approaches. Fig. 7 depicts, for HOMER® Grid, the temporal evolution of PV output (red), internal load (green), grid purchase (purple) and grid sales (light blue), as well as

Table 2
Yearly energy balance of the HOMER® Grid reference system.

HOMER® Grid – Energy Balance					
12,849 EVs charged					
Production	kWh	%	Use	kWh	%
Generic flat plate PV	231,311	77.7	AC Primary Load	36,500	12.4
Grid Purchases	66,425	22.3	Grid Sales	61,257	21.0
			EV Charger Served	194,702	66.6
Total	297,736	100	Total	292,459	100

Table 3
Yearly energy balance of the SPEM reference system.

SPEM – Energy Balance					
12,849 EVs charged					
Production	kWh	%	Use	kWh	%
Generic flat plate PV	236,443	80.0	AC Primary Load	36,500	12.2
Grid Purchases	59,615	20.0	Grid Sales	74,810	25.3
			EV Charger Served	184,747	62.5
Total	296,058	100	Total	296,057	100

Table 4
Comparison of key numbers of the HOMER® Grid and SPEM modeled systems.

March 25–31	Nr of EVs	Total from PV (kWh)	Total energy for EVs charge (kWh)	Total energy purchased (kWh)	Total energy sold (kWh)
HOMER®	309	4819	4319	1643	1265
SPEM	313	4993	4648	1715	1560

charging load dedicated to EV batteries (dark blue); Fig. 8 shows the equivalent data for SPEM.

Fig. 9 represents a direct comparison between the modeled PV output over time for both simulations, Fig. 10 compares the temporal evolution of the total EVs charging power, and Fig. 11 the temporal evolution of the grid purchases.

The PV output curves are very similar, despite small differences due to the fact that HOMER® Grid uses hourly data and SPEM data on a 15-min basis. The other curves differ slightly because the management of the charging is different, and the mobility input data are slightly different. As described in Section 3.1, SPEM uses real historical reference data, while HOMER® Grid uses a statistical distribution that resembles the reference situation as closely as possible. As a result, the exchange with the grid and the use of the BESS are also different.

A closer look at Figs. 7–10 shows how the management algorithm of SPEM, based on PV production and forecast, shifts the charging power to the afternoon when the solar irradiation is higher, better overlapping with PV production. This has the positive result of avoiding grid purchases in the early hours of the day and better balancing the exchange with the grid, as can be seen in Fig. 10. The plateau in the grid purchase curves (Fig. 11) is associated with the grid power demand limit of HOMER® (55 kW in present analysis) that restricts the maximum allowable grid purchase.

3.5. Charging stations management

In smart or deferrable charging station mode, HOMER® Grid prioritizes the use of renewable power and schedules charging to take advantage of grid electricity when it is at its lowest cost. Homer® Grid does not allow to set and control every single charging session; the software assumes an average daily number of EVs entering the parking lot distributed on a weekday based hourly function. Moreover, it charges all EV batteries once in process of charging continuously and with constant charging power, resulting in a linear increase of the SOC for each of the EVs. This behavior can be observed in Fig. 12, which shows the SOC of a Tesla Model 3 over time, where the battery is charged at the user defined maximum output power of the charging station of 7 kW, for a charging time of 7.5 h; the software allows to define an average charging time, here set in 8 h per EV, with an allowed variability of 20%. The same global presets hold for all 61 charging sessions depicted in Fig. 13, representing HOMER® Grid's daily profile view of March 27.

SPEM conducts the charging station management in a more granular way, deferring charging requests according to renewable energy availability; in addition, it can adapt in real-time the total charging power and its distribution amongst the EVs present in the parking lot. The optimization of energy distribution depends on the solar forecast and EVs parking time through prioritizing cars with higher energy needs and reducing the energy supply to those EVs with longer remaining time. To demonstrate this, Fig. 14 shows the behavior of five different charging stations associated with five different types of EVs with 28, 30, 33, 36 and 60 kWh battery, obtained from SPEM simulation. Fig. 14 demonstrates that charging is not always a linear process due to modulations of the charging power following PV production and parking occupancy. The two segmented lines on Tuesday 26th Thursday 28th represent different EVs occupying the same charging station.

The presented comparison between SPEM and HOMER® Grid serves as a qualitative benchmark but cannot be seen as a one-to-one comparison, since the test cases are not identical. There are several differences:

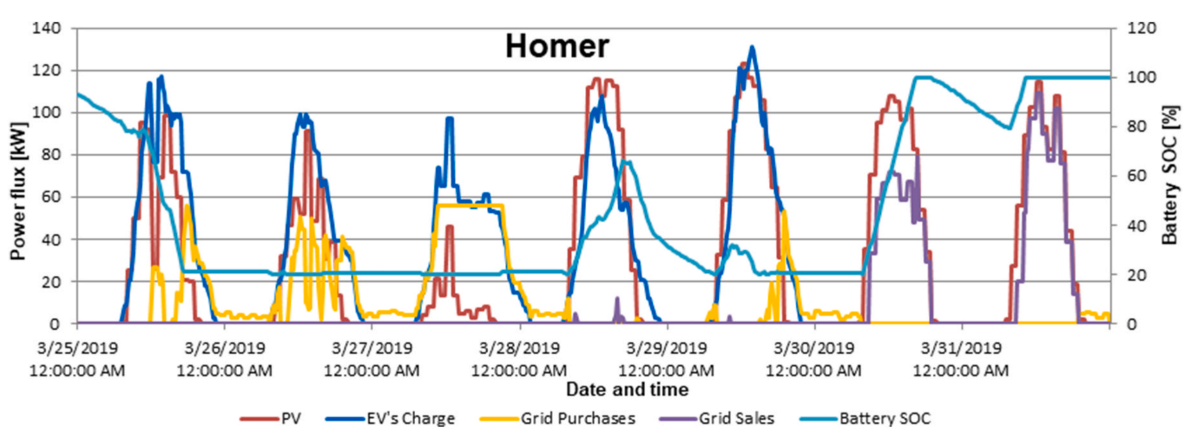

Fig. 7. One week time evolution (March 25–31, 2019) of the power fluxes profile output from HOMER® Grid simulation. The different curves depict: the temporal evolution of power fluxes from PV (red), from grid purchase (yellow) and to grid sales (purple), the power provided for EV batteries charge (dark blue), BESS state of charge (light blue - on the right scale).

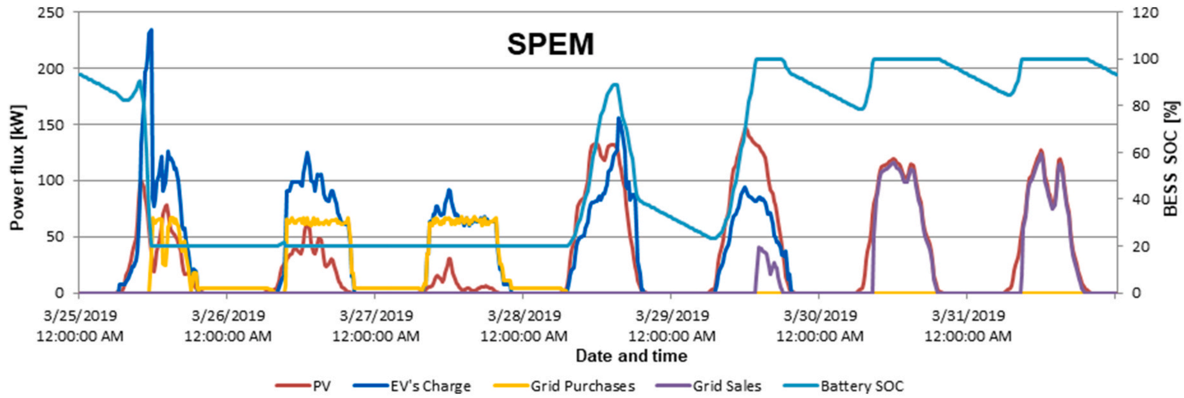

Fig. 8. One week time evolution (March 25–31, 2019) of the power fluxes profile output from SPEM design simulation. The different curves depict: the temporal evolution of power fluxes from PV (red), from grid purchase (yellow) and to grid sales (purple), the power provided for EV batteries charge (dark blue), BESS state of charge (light blue - on the right scale).

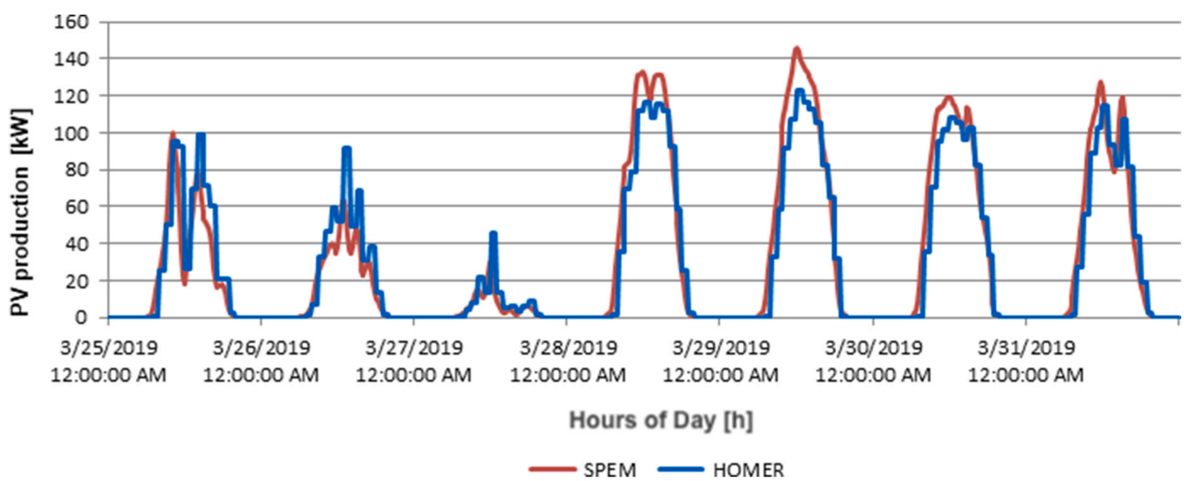

Fig. 9. The modeled PV output time evolution (March 25–31, 2019) in both simulations.

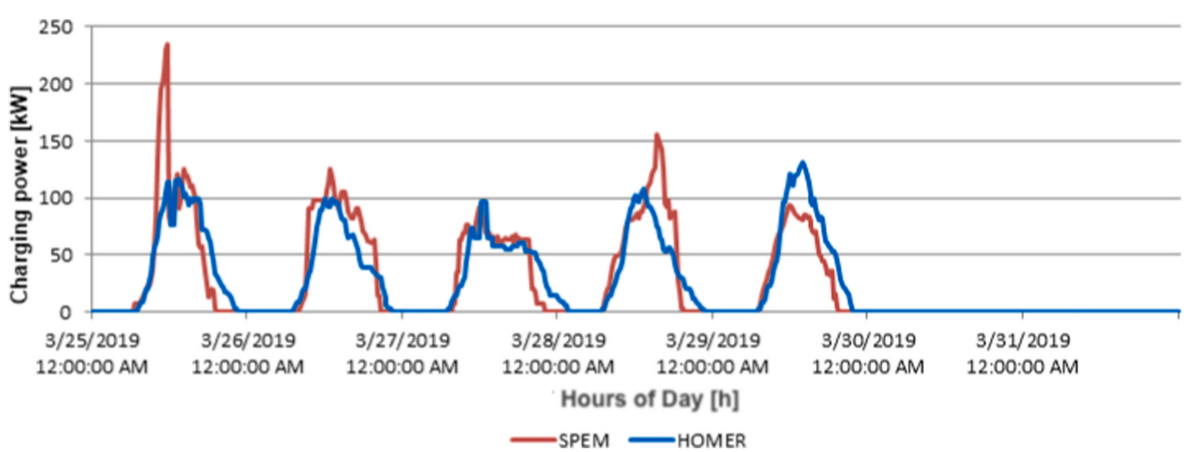

Fig. 10. Time evolution (March 25–31, 2019) of the total EVs charging power in both simulations.

(1) **Data**: HOMER® Grid uses for workdays a user-defined mobility table that defines EV arrival numbers by daytime and month. A separate table exists for the weekends. Furthermore, HOMER® Grid allows global user-defined random variations to these mobility data. Bank and local holiday periods that strongly influence real data, cannot be represented in the statistical description of the HOMER® mobility profiles. On the contrary, SPEM works with the real mobility data, which is updated for every time step.

(2) **Optimization**: SPEM optimizes the energy flows time step to time step based on forecasts, while HOMER® Grid optimizes energy flows based on the exact knowledge of future occupancy, EV charging demand and PV energy supply.

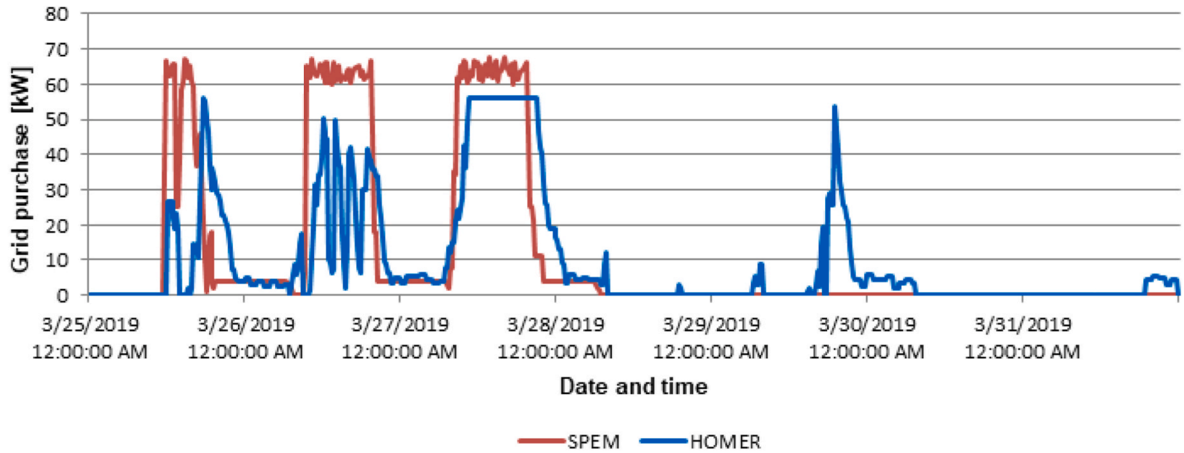

Fig. 11. Time evolution (March 25–31, 2019) of the grid purchases in both simulations.

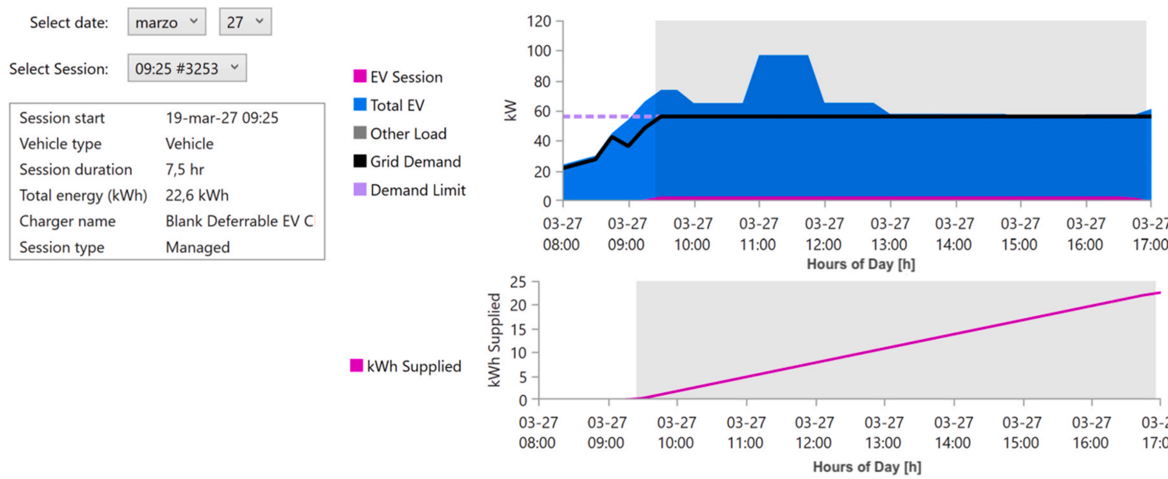

Fig. 12. Screenshot from HOMER® Grid, showing a single session view, referring to the charging of a single EV (Tesla Model 3). The upper graph shows the power demand of this single session (pink), the total power dedicated to EV charging (blue), the grid demand (black), other demand (gray) and the demand limit (dotted purple). The lower graph shows the SOC of the battery of the EV during parking time.

(3) **Charging method**: Another important difference between the two approaches is related to the intrinsic definition of the charging algorithm of SPEM that is designed to modulate the power of the charging columns - and of the BMS - to optimize the charging strategy.

It is worthwhile to underline that the assumption of perfect knowledge of the PV generation as well as the mobility energy demand over the whole period of simulation lead to a result that is an upper limit of the performance of the simulated charging strategy [32].

4. Economic analysis

The SPEM platform's real-time operational mode was created to combine instantaneous information on energy fluxes with electricity purchase and sale prices, allowing parking managers to create optimal tariffs tailored to the needs of each customer.

A detailed analysis, which includes every possible option for the various components of such a complex system is a lengthy process that lies outside the scope of this paper, particularly since the final Levelized Cost Of Energy (LCOE) used for vehicle charging and the economic fluxes are also strongly dependent on the available local energy purchase and sale costs. The LCOE, in fact, not only depends on the size and type of the involved technologies, such as BESS, PV panel, converters and charging stations, but is strictly linked to buy/sell prices of electric energy, maximum demand charge, incentives and specific electricity supply contracts.

For these reasons, an economic assessment produced specifically for the analyzed test case of CRS4 and based on the previously discussed SPEM design simulation with historical database, is presented here. This rough analysis can provide only a preliminary indication of the trend in actual costs, assuming average cost for the involved technologies and electricity purchase and sale cost, evaluating the sensitivity of final LCOE to the variation of the reference average values choice.

In particular, the electricity price fluctuations and eventual feed-in-tariff revenues are variables subject to strong variations of local conditions in which they are considered. In this preliminary evaluation obtained through the SPEM design mode, electricity prices are assumed to be constant during the whole period of the simulation; on the other hand, their complete and detailed profiles are continuously updated during the SPEM real-time mode, allowing an instantaneous definition of the preferred electricity tariff.

Assuming the values given in Table 5, the LCOE of one auto-produced kWh, i.e., the final cost net from the energy exchanges with the grid is:

$$\mathrm{LOCE_a} = 0.078\ €/\mathrm{kWh}$$

While the final LCOE resulting from the net energy balance of the

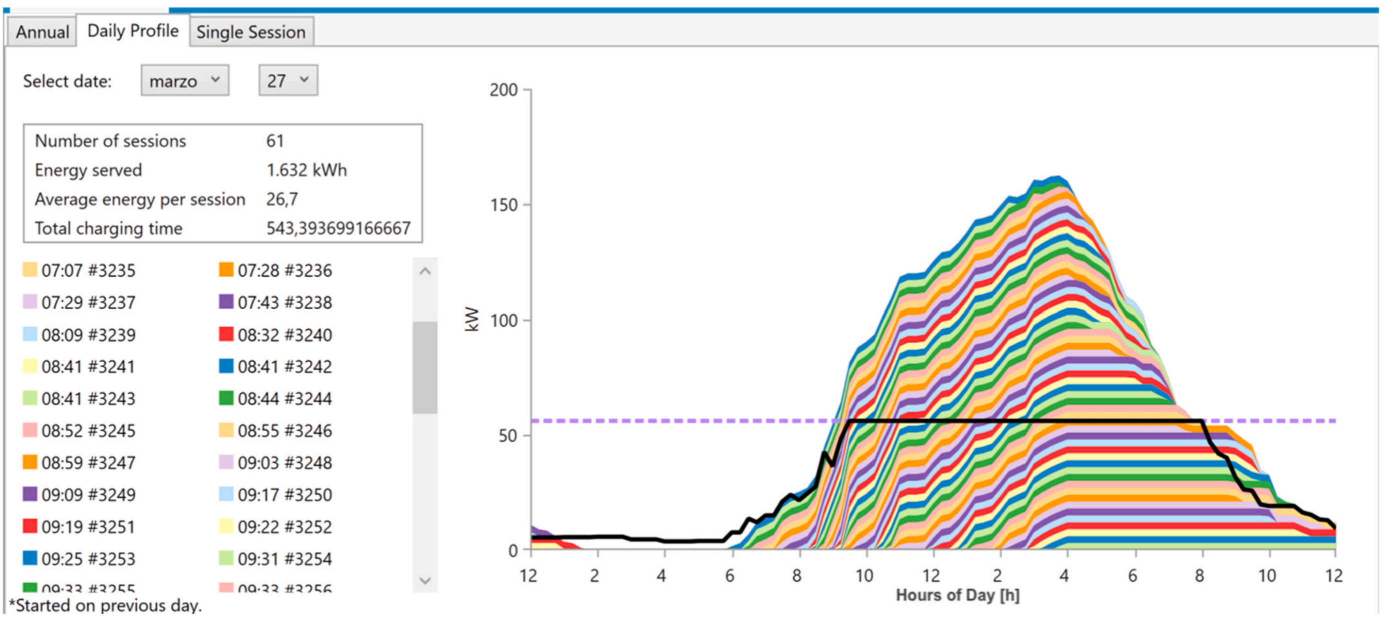

Fig. 13. Screenshot from HOMER® Grid, showing daily profile view of March 27. On this day 61 EVs are being charged. Color code, starting time and session number of the earliest sessions are given on the left. On the right all these charging sessions are shown (multiple colors) together with the grid demand (black) and the grid demand limit (purple).

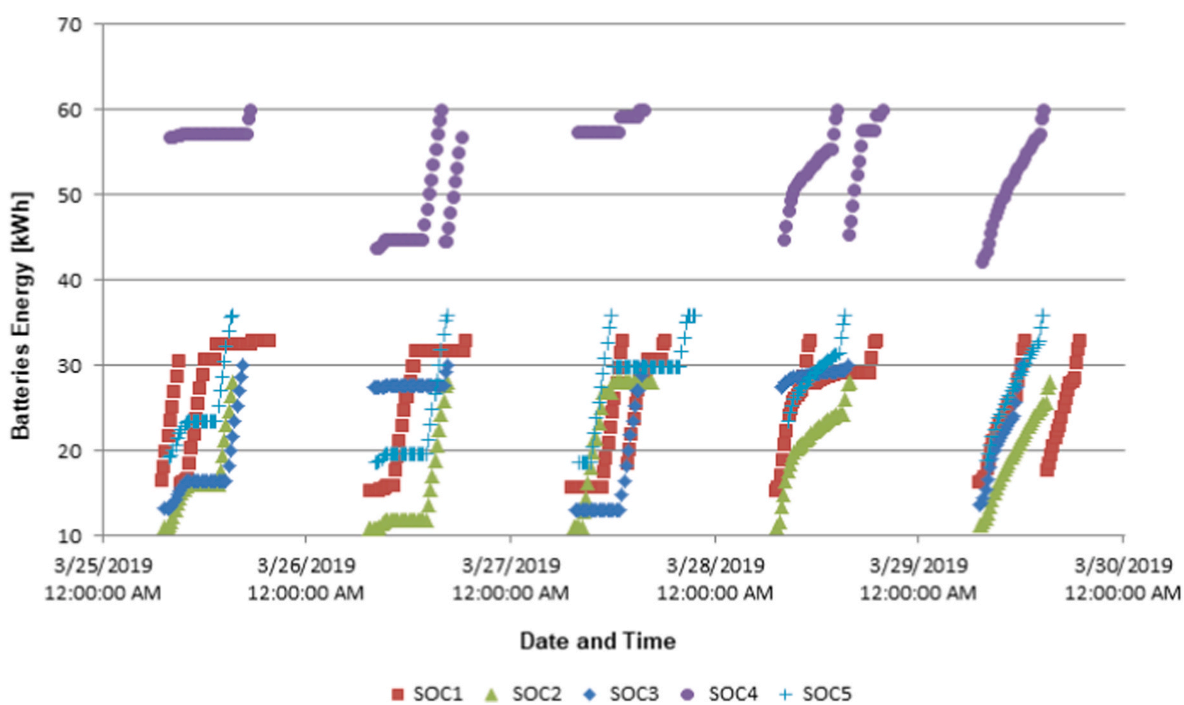

Fig. 14. SOC behavior of five different types of EVs with 28, 30, 33, 36 and 60 kWh battery associated with five different charging stations, obtained from SPEM simulation. Five working days (March 25–29, 2019) are represented; two different lines on the same days represent two EVs occupying the same slot.

parking, including the exchange with the grid, is:

$LOCE_f = 0.220$ €/kWh

This high increase in the final cost of the energy unit is mainly due to the unfavorable grid exchange. Due to the high volatility of the market, internal evaluation, at the moment of the drafting of this paper (August 2022), leads to an average purchase cost of 0.5 €/kWh, while the selling price has been set to 0.15 €/kWh.[4]

To analyze price sensibility, the variations of the final $LOCE_f$, resulting from a ±50% variation of the costs for crucial economic factors, are displayed in Fig. 15 in the form of a tornado diagram. Length and color of the horizontal bars represents the $LOCE_f$ changes for different price determinants, ordered by the size of the change. It is

[4] https://www.mercatoelettrico.org/Newsletter/20220812Newsletter.pdf.

Table 5
Reference cost/price of involved variables.

Technology	Unitary price (€)	unit	Source
PV	870	kW	Danish Energy Agency [57]
BESS	137	kWh	Bloomberg [58]
Converter	75	kW	HOMER® [40]
Charging station	500	unit	Internal evaluation
Commissioning	10	% of CAPEX	Internal evaluation
Electricity purchase price	0.50	kWh	Internal evaluation
Electricity selling price	0.15	kWh	Internal evaluation
OPEX	3367	year	Danish Energy Agency [57]

evident that the dominating variable is the electricity purchase price (including all costs and tariffs) and the final cost of installed PV.

5. Conclusions

This paper presented the SPEM IoT platform, capable of simulating, designing and real time managing the smart charging of EV fleets in a RES-E driven parking lot.

A deterministic rule-based algorithm was introduced for the fine-grained management of the energy fluxes between EVs and the different electric components of a solar parking lot. Since the algorithm does not utilize any assumption on the future mobility and energy demand it can handle unforeseen changes avoiding critical situations.

As it was shown, intra-day deferral serves to shift EV charging demand towards the time of maximum production, guided by MPC, constantly analyzing the momentary situation of 1) intermittent solar production, 2) stored energy and energy storage availability, 3) charging station occupancy and 4) solar production forecast.

An extensive case study was conducted, where the design mode of SPEM was applied to the historic situation of an Italian Research Center in 2019, assuming the substitution of all employee's cars by EVs. As a benchmark for the validation of SPEM, HOMER® Grid, a commercial software for the modeling, design and simulation of electrical infrastructure, was used.

As it was discussed in detail, the two software tools follow different strategies regarding model description and smart charging method. Nevertheless, the simulation results of the two approaches are in good agreement.

The analyzed scenario operates as much as possible in island configuration, i.e., minimizing two quantitative objectives such as the energy exchange at PCC and the peak power demand from the external grid.

Albeit affected by simplified assumptions regarding the costs/prices of energy, the provided preliminary economic analysis for this scenario, shows the effectiveness of this approach, paving the way for a successful use of the real-time operational mode in tariffs design.

CMC-IoT provides SPEM with an interface to real-word sensors and actuators. The latter allows to not only model complex systems with simulated hardware, but to be connected to real physical hardware which can then be controlled in real-time. The most innovative feature of the proposed power control system is connected to the possibility to use a high-level and general-purpose platform, built upon a microservice architecture and conceived for supporting the development of vertical services and applications. This approach gives the opportunity to interface with innovative equipment and energy-storage devices, whose energy load requires unconventional management of power distribution, with the objective of programming or deferring their operating functions based on the PV power production forecast.

Although the reference case analyzed in this paper has well-defined features, characterized by the presence of vehicles in the working hours range, the use of the microservices approach allows the platform to be robust and flexible enough to be easily scalable and replicable in different contexts and application scenarios.

The presented case study was limited to the application of the design mode. The strong agreement with the results of HOMER® Grid validates the design mode of the SPEM IoT platform as an appropriate tool for simulation. The real-time operational mode is based on the same algorithms but controls real hardware components instead of simulated ones.

This gives the indication that the operation of SPEM in the real-time mode, through IoT support, can be seen as a valid candidate for the

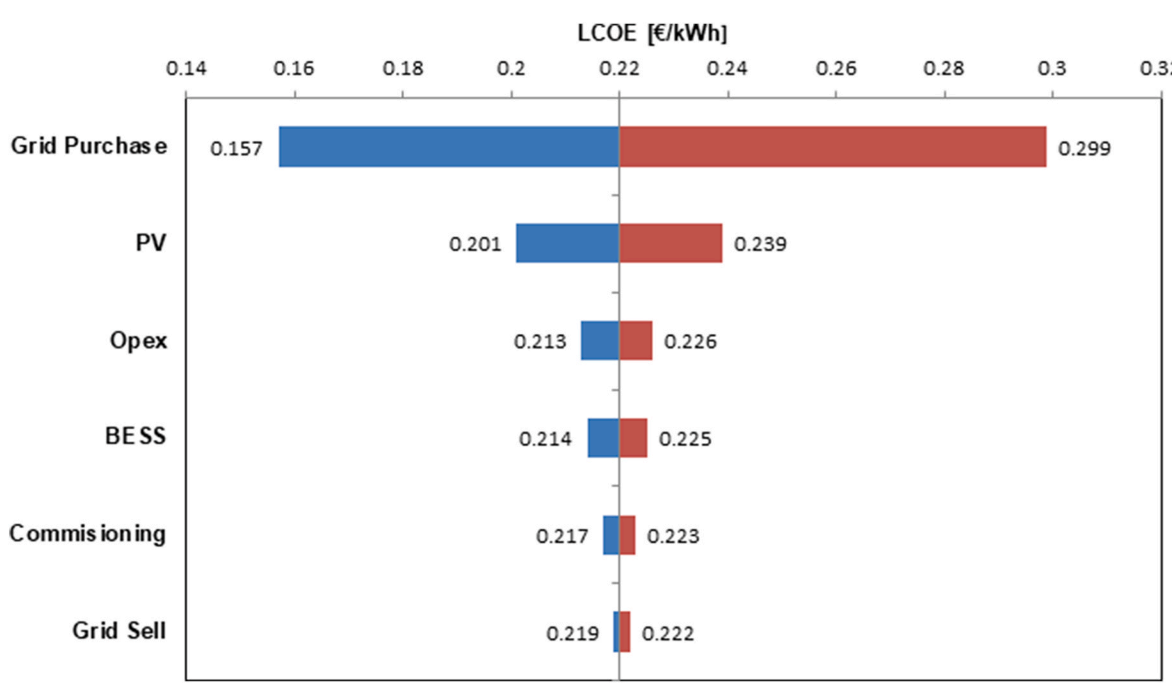

Fig. 15. Tornado diagram representing sensitivity analysis of ±50% variation from reference values to the final LCOE.

optimal management of a real solar parking lot.

Currently, a small-scale physical model of such a parking lot is under development. This will be the proximate step to validate the real-time mode of the SPEM IoT platform. Finally, the intention is to develop a full-size demonstrator, e.g., by installing a SPEM controlled group of EV charging stations at the research center where the case study was conducted, which already hosts a solar power plant of sufficient size. Having a practical use case, it will be possible to start developing, as appropriate, more advanced features, such as dispatchable demand, demand management pricing, cross-segment optimization, V2G or even V2V.

CRediT author statement

Alberto Varone: Conceptualization, Writing - Original draft preparation, Software, Methodology, Resources, Zeno Heilmann: Software, Writing - Original draft preparation, Investigation Methodology, Writing - Review & Editing, Alessandro Romanino: Formal analysis, Resources, Writing - Review & Editing, Software, Guido Porruvecchio: Formal analysis, Resources, Writing - Review & Editing, Software.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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